2007

Does It Matter Which Process Modelling Language We Teach or Use? An Experimental Study on Understanding Process Modelling Languages without Formal Education

Jan Recker
Queensland University of Technology, jan.christof.recker@uni-hamburg.de

Alexander Dreiling
SAP Research CEC Brisbane, alexander.dreiling@sap.com

Does It Matter Which Process Modelling Language We Teach or Use? An Experimental Study on Understanding Process Modelling Languages without Formal Education

Jan Recker
Business Process Management Cluster
Queensland University of Technology
Brisbane, Australia
Email: j.recker@qut.edu.au

Alexander Dreiling
SAP Research CEC Brisbane
Brisbane, Australia
Email: alexander.dreiling@sap.com

Abstract

Process modelling has over the years become an essential skill in Information Systems and Business Process Management practice. Consequently, more and more training programs have evolved, teaching different process modelling languages. Two popular process modelling languages are being compared in this experimental study. Experiment participants received extensive training in one language but not the other, leading to the expectation that learning outcomes would be better in the case of the familiar language. Our study provides empirical evidence that this is not the case. In fact, it is shown that participants achieved similar learning outcomes when confronted with the unfamiliar language. Our results lead to a fundamental question, namely whether it is actually an important teaching decision what sort of process modelling language is being taught. Our findings suggest that education and research in process modelling should focus on aspects other than the style, nature or features of languages and tools.

Keywords

Process modelling, BPMN, EPC, cognitive theory, experiment

Introduction

The increased popularity of process modelling in IS and BPM practice over the past few years has put quite a burden on educational institutions. In order to reply to the increasing market demand for business and technical analysts equipped with process modelling skills, a range of interesting questions have to be answered by academia and practice out of which three are (1) Which process modelling language should be taught in tertiary educational institutions in order to account for the market demand of graduates being skilled in process modelling? (2) Should multiple languages be taught in formal education? (3) Which process modelling language should a vendor of a BPM tool support, or should a vendor even create yet another language – and what are the implications of making such a decision?

These questions have massive economic impact. Setting on the "false" process modelling language may lead to business failure, and teaching the wrong language may result in not serving the market demand appropriately, which leads to additional investments of companies to up-skill university graduates.

As of today, the process modelling discipline has been coined by fragmentation in the choice of languages used for teaching, tools and practice. The range of process modelling languages available spans simple flowcharting techniques, languages initially used as part of requirements engineering such as UML (Fowler, 2004), dedicated business-oriented modelling languages such as Event-driven Process Chains (Scheer, 2000), and also formalized and academically studied languages such as Petri nets (Petri, 1962) and their dialects. Consequently, a competitive market is providing a large selection of languages and tools for process modelling (Sinur, 2004), significant demand has been created for means to evaluate and compare the available set of languages (Moody, 2005) and almost every educational institute offers process modelling courses focusing on different languages.

Recently, yet another process modelling language was introduced, the Business Process Modeling Notation (BPMN) (BPMI.org and OMG, 2006). Interestingly, it has gained unprecedented momentum in academia and practice. More and more universities offer BPMN in their curriculum, tools for modelling BPMN enter the market and research on BPMN becomes increasingly available. BPMN offers a great vision in that it is meant to be a language understandable to business users yet formal and expressive enough to be transformed into an executable or machine-interpretable language such as BPEL. Also, it comes with huge advantage of being put forward as an industry standard for process modelling.

However, every new language comes at the cost that a language community has to emerge first before any benefits can be derived from it. There are many examples of languages that seem preferable from an academic perspective, e.g., YAWL (van der Aalst and ter Hofstede, 2005), but that never experienced a significant uptake or even disappeared because they failed to build up a sustainable group of language users.

In the case of BPMN, this observation leads to decisive managerial implications for organizations seeking to adopt BPMN for their process management initiatives. The huge demand for BPMN process modelling stands in sharp contrast to the paucity of process modellers equipped with BPMN modelling skills. Because of its recent release coupled with the unprecedented uptake in academia and practice, many organizations are in the uncomfortable situation of having to rely on business and technical analysts that have no experience in BPMN, but instead in a different language. The question that arises for organizations then is how costly it will be to train the existing analysts in the new language. Consequently, and not surprisingly, a range of training providers have emerged over the last couple of months offering training services in BPMN. The rationale for explicit BPMN training is quite simple. Hypothetically, a more complex language will have even more difficulties in getting established and used as the complexity poses a decisive barrier for new users. Hence it would appear that there is indeed a good rationale for organizations to undertake extensive, and costly, BPMN training to its set of analysts even though these may have had prior process modelling knowledge – in a different language.

Our interest is to understand the processes of teaching and learning process modelling languages. In particular, we seek to understand how individuals develop an understanding of process models, even if they have never been confronted with the language in which it is depicted. Accordingly, the explicit aim of this paper is to examine empirically whether there are differences in the understanding of a process model that are depicted in a familiar versus an unfamiliar language. To that end, in this paper we report on the design and conduct of an experiment with users that have received extensive training in one popular process modelling language, EPCs but not in a second, that is, BPMN.

We will proceed as follows. In the next section we will introduce theories and concepts relevant to our research, i.e., learning from process models. We will then outline a range of hypotheses, followed by a discussion of our research method. Finally, we will present our results, discuss them and introduce a range of implications.

Theory and Hypotheses

In order to be able to measure differences in learning process modelling languages, we refer to the cognitive theory of multimedia learning as a theoretical background on which hypotheses about learning process modelling can be established. In the following we will introduce this theory and then discuss the hypotheses derived from it.

Cognitive Theory of Multimedia Learning

We use the Cognitive Theory of Multimedia Learning (CTML) by Mayer (1989; 2001) to explain how individuals viewing explanative material (such as a process model) develop understanding of content being presented to them. We chose CTML for several reasons. First, it focuses on words and graphics, which in fact are elements in any process modelling language. Second, it provides principles for the design of effective content presentations in the form of textual and/or graphical descriptions (i.e., a model) that can be tested empirically. Third, there is an established track record of experimental studies in conceptual modelling that has successfully used CTML to establish empirically observable differences in studies of conceptual modelling languages, e.g., in the data modelling domain (Bodart *et al.*, 2001; Gemino and Wand, 2005).

CTML suggests three outcomes are possible when presenting explanative material in the form of models: (1) no learning, (2) fragmented learning and (3) meaningful learning. These outcomes are primarily based on measures of two variables that Mayer (2001) labels *retention* and *transfer*. Retention is defined as the comprehension of material being presented. Transfer, or problem solving as it will be referred to in this paper, is the ability to use knowledge gained from the material to solve related problems not directly answerable from it. For example, if presented with an explanation of how a car's braking system works, a comprehension question might be "What are the components of a braking system?", but a problem solving question would be "What could be done to make brakes more reliable?" No learning occurs where comprehension and problem solving are low. Fragmented learning occurs where comprehension is high but problem solving is low. Such result indicates material has been received but has not been well integrated with prior knowledge. This suggests memorization rather than meaningful learning has occurred. Finally, meaningful learning occurs when both comprehension and problem solving are high. High problem solving indicates information has been integrated into long-term knowledge and a high level of understanding of the presented material has been achieved.

Applying these premises to the context of learning process modelling languages, one key objective of teaching process modelling languages would obviously be to enable meaningful learning. Given that a process model is in its essence a graphical description of real-world business domains, meaningful learning to read these models should enable a process modelling language user to understand and reason faithfully and appropriately about the business domain that is depicted in a process model.

Hypotheses

Mayer (1989) suggests three elements that are involved in the process of constructing knowledge (i.e., learning) from explanative information, such as, in our case, process models (see Figure 1):

(a) the content of the message, viz., the business content of the process model

(b) the way in which the content is presented, viz., the capabilities of the process modelling language to depict the business content

(c) the individual characteristics of the person viewing the model, viz., the process model user

These three elements interact in forming knowledge construction, which is a cognitive learning outcome. One way of measuring the learning outcome is by using learning performance indicators such as the problem solving and domain comprehension, as described above. One way of measuring user characteristics is to elicit user differences, for instance, in levels of domain and modelling experience (Gemino and Wand, 2005). One way of measuring differences in content presentation is to use languages with different levels of expressive power or different forms of visualization.

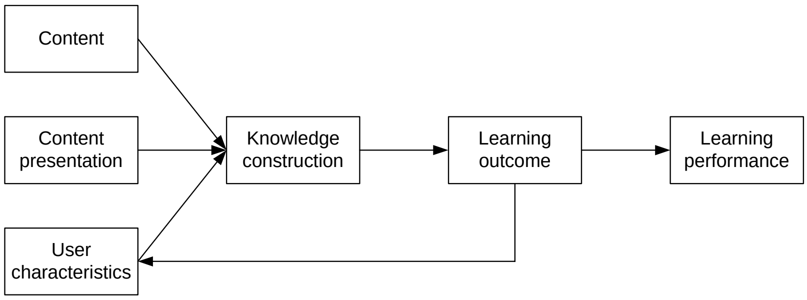

Figure 1: A model for knowledge construction in process modelling. Adapted from (Mayer, 1989) to the process modelling domain

Our main hypothesis stems from the simple observation that a model viewer that is presented a process model depicted in a language she has been taught before would have higher learning performance than someone who is given a process model depicted in a language she is unfamiliar with. The rationale for this observation is quite obvious. The more experienced someone is in using a certain language for modelling the better is her understanding of the content depicted in these models. There is simply no substitute for experience (Jarvenpaa and Machesky, 1989; Batra and Davis, 1992).

Another rationale for this hypothesis stems from the observation that humans have limited cognitive capacity (Siau, 1999; Gemino and Wand, 2005). This suggests that a process model is unlikely to be absorbed as a "whole" but rather understood in small pieces. Similarly, it suggests that process models with more *apparent complexity* are harder to absorb and understand than models with less apparent complexity. Apparent complexity is a term used in experimental research on conceptual modelling that refers to a measure for the complexity of a model or modelling language expressed in number of different language constructs used (Gemino and Wand, 2003). Simply put, a language with a more differentiated set of language constructs provides more expressive power. This, however, comes at the extent of increased apparent complexity because language users have to understand and distinguish a larger set of semantically different constructs.

We have taken the examples of the two languages Event-driven Process Chains (EPC) (Scheer, 2000) and Business Process Modeling Notation (BPMN) (BPMI.org and OMG, 2006). These two languages arguably differ in terms of their complexity. EPCs consists of a mere nine language constructs., viz., events, functions, process interfaces, assignments, organizational units, arcs, and XOR, AND, OR connectors whereas BPMN provides a set of thirty-nine language constructs. One would assume, naturally, that it is easier to come to grips with, and develop expertise in the usage of, nine language constructs rather than thirty-nine. This suggests that students that have extensively been trained in EPCs but not BPMN, ceteris paribus, would have higher learning outcomes when confronted with EPC models than with BPMN models. Therefore, we have

H1: Learning performance will be higher for the EPC group than for the BPMN group.[1]

It is difficult to measure learning performance directly. Typically, two measures are used – problem solving and Cloze scores. Problem solving scores are a measure of domain understanding because these questions require reasoning about the domain where the answers are not directly represented in the model (Mayer, 1989, 2001). It has in several modelling experiments been found to be an adequate measure, e.g., (Bodart *et al.*, 2001; Gemino, 2004; Gemino and Wand, 2005). Given that EPC students obviously have a higher expertise in reading EPC models and one would thus expect that the conveyed domain information is more easily extracted and applied, we have

H1a: Problem solving scores will be higher for the EPC group than for the BPMN group.

Another element of learning performance can be measured by a Cloze test (Taylor, 1953). In a Cloze test, participant receive a passage to read in which some of the words are missing and need to be filled in. The more blanks filled in, the better the understanding of the 'meaning' of the missing word, with focus placed on the semantics of the overall passage (Greene, 2001). Cloze tests outperform traditional comprehension tests in that instead of single words, the recognition of the cohesive device that makes a carefully constructed argument possible is tested (Rankin and Culhane, 1969). Since a Cloze test is based on the business domain and not the model itself and since a language that has less apparent complexity and with which users are more familiar with provides more readily understandable semantics, our second sub-hypothesis states:

H1b: Cloze scores will be higher for the EPC group than for the BPMN group.

An important design consideration in the comparison of conceptual models is the notion of informational equivalence (Siau, 2004). Comparison results may be biased simply because one of the models under observation conveys more information than the others, leading to better learning outcomes for the informational superior model. It is important, therefore, to establish that the models used in the comparison approximately contain the same amount of information. Since informational equivalence is difficult to establish theoretically, we follow (Gemino and Wand, 2005) and measure it empirically by means of a simple multiple-choice comprehension test. The questions in such a test are solely focused on the elements provided in the models. If the models are informationally equivalent, all groups should score similarly, hence we have:

H2: Model comprehension will not differ between the EPC group and the BPMN group.

A related yet different notion is that of computational equivalence (Siau, 2004). Just because models in different languages are informationally equivalent does not make the models equally understandable. A model that holds a computational advantage over another presents the same information in a manner that is easier to integrate in the knowledge construction process, viz., learning occurs faster. Again, one would assume that increased familiarity and lower apparent complexity of a language would result in advantage, therefore:

H3a: Model comprehension tasks will be completed faster by the EPC group than by the BPMN group.

H3b: Problem solving tasks will be completed faster by the EPC group than by the BPMN group.

H3c: Cloze tests will be completed faster by the the EPC group than by the EPC BPMN group.

Research Method

Setup

We followed a design previously developed and used by Bodart et al. (2001) as well as Gemino and Wand (2005) in experiments with data models. The experiment material consisted of an information cover sheet with consent form, one page of directions, two model cases and several sheets with questions and textboxes for answers. Participants had knowledge of EPCs but not BPMN. No introduction or training on BPMN was conducted prior to conduct. Participants were informed that test times were being recorded but were given as much time as required for task completion. The two cases used in the experiments differed only in their representational complexity (Bodart *et al.*, 2001), i.e., in the number and semantics of elements in the model.

Participants

In the EPC-BPMN experiment, overall 69 postgraduate Information Systems students participated who had all taken at least one course in business process management and modelling with EPCs but did not have any knowledge of BPMN. Even though a choice of students for experiments has sometimes been criticized for lack

[1] Here and in the following, 'EPC group' refers to the group of participants that is confronted with an EPC model in the experiment and the 'BPMN group' refers to the group of participants that is confronted with a BPMN model.

of external validity, we agree with Gemino and Wand (2004) and Batra et al. (1990) that the selection of students over practitioners in this type of research can in fact be advisable. Results from both domain understanding and problem solving tasks could have been confounded by participants that are able to bring to bear prior business knowledge in one of the areas (Siau and Loo, 2006). Hence, the selection of students overcomes the problem of controlling for any bias in technique or domain familiarity.

Participants were randomly assigned to one of two treatment groups. Participation was voluntary and as incentives the students were upfront offered the chance of participating in a draw for one of several course books. The test was monitored to assure individuals completed the test independently.

Design

One treatment group first received a model depicted in the language they are familiar with (i.e., EPC), the other group first received a model depicted in the unknown language (i.e., BPMN).

The experimental procedure began with a pre-test of domain knowledge and modelling experience to ensure equivalency between the treatment groups in terms of user characteristics (see Figure 1). Then, each participant completed the cases 'Goods receipt' and 'Claims handling'.[2] Table 1 summarizes the differences between the models and highlights the differences between EPC and BPMN in respect of the apparent complexity of the models. It shows that the EPC models were made up by a very limited number of different language constructs that, however, appear multiple times in the same model. BPMN uses more different constructs to build models that overall contain less constructs. This indicates that the BPMN constructs are semantically more expressive than the EPC constructs (you have dedicated constructs to depict, let's say, a looping of activities, which, in the case of EPCs, would be modelled by a range of simple constructs), which in turn suggests that the semantics of the BPMN constructs are more differentiated and hence more complex than in the case of EPC.

Table 1: Complexity of the process models for each case

Measure	Goods receipt EPC	Goods receipt BPMN	Claims handling EPC	Claims handling BPMN
Number of language constructs overall	27	27	44	36
Number of semantically different language constructs	4	10	6	13

For each of the cases, participants completed three tasks in the following order: model comprehension, problem solving and cloze test. A post-test was provided after the cloze test of the second case to measure perceived ease of understanding associated with the languages used. The overall procedure is shown in Figure 2. A subsequent ANOVA procedure showed that case order did not affect test scores.

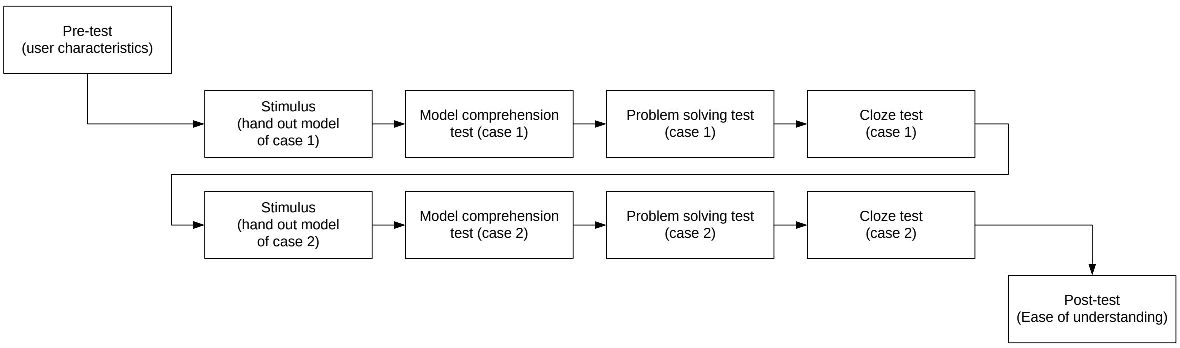

Figure 2: Overview of experiment design

Model comprehension was measured using a set of multiple-choice questions were participants were asked to recall basic features of the process model presented. For each question, participants were instructed to fill in 'Yes", "No", "Undecided" or "cannot be answered from the model". Problem solving was measured by giving the participants three business scenarios based on the business domain depicted in the process models and asking them to provide plausible solutions to the problem presented in the scenario. In developing these questions, the guidelines of Bodart et al. (2001) were followed in distinguishing three types of answers: (a) the number of plausible answers based on information inferable from the model, (b) the number of plausible answers that showed knowledge beyond the information provided in the model, and (c) the number of implausible or missing answers. Answers of type (b) can be seen as an empirical indicator for meaningful

2 Case descriptions are available upon request, as are the models and test questions.

learning. The Cloze test consisted of a textual description of the process depicted in the model with some of the words missing. Participants were asked to fill in the blanks based on their understanding of the process model.

Additional Independent and Control Variable

A pre-test was used to collect information on participant's familiarity, confidence, and competence with the EPC modelling language, as well as their perceived knowledge of business process management domains. These questions were used to create scale variables for the level of modelling experience, and the level of domain knowledge. The scale variables were later used as covariates in the hypothesis testing exercise. As well, a post-test was conducted for measuring perceived ease of understanding. The scale was adopted from the ease of use scale developed by Moore and Benbasat (1991).

Times taken to complete tasks are an objective measure often used to indicate the degree of difficulty or complexity in using a method (Jarvenpaa and Machesky, 1989). Thus, time taken to complete each of the three experimental tasks (comprehension, problem solving and Cloze) was also measured.

Results

Two research assistants were employed to code the responses received from the experiment. These research assistants were not informed about the purpose of the study to ensure coding independence. To establish coding reliability, both researchers first individually coded the responses and then met to defend and discuss their coding to generate a final, consensually agreed coding result.

Hypothesis testing was completed using an analysis of covariance (ANCOVA) technique and performed with SPSS 13.0. The ANCOVA technique was chosen so as to be able to control for the intervening variables *level of EPC competency* and *perceived business domain knowledge* (Stevens, 2001). For all cases and dependent variables, these covariates did not affect test scores significantly, suggesting that prior modelling experience and domain knowledge has no significant effect on the experiment results. This outcome can partly be accredited to the choice of students over practitioners so as to control for varying levels of expertise and knowledge. For the sake of brevity and clarity, estimated coefficients and test statistics for the covariates are left out of the statistics below. Results for hypotheses H1a (problem solving), H1b (Cloze test) and H2 (model comprehension) are summarized in Table 2.

Table 2: ANOVA results for dependent variables in the experiment across the EPC and BPMN groups

		Case: Goods receipt			Case: Claims handling		
Measure	Group	Means	Standard deviation	F (Sig.)	Means	Standard deviation	F (Sig.)
Model comprehension (correct answers)	EPC (n=34)	4.260	1.053	3.167 (0.080)	4.350	1.756	0.132 (0.718)
	BPMN (n=35)	3.770	1.239		4.200	1.746	
Problem solving (acceptable inferred answers)	EPC (n=34)	1.650	1.178	0.020 (0.887)	1.470	1.212	2.972 (0.154)
	BPMN (n=35)	1.690	1.078		1.890	1.183	
Problem solving (acceptable model-based answers)	EPC (n=34)	0.500	0.749	2.185 (0.144)	0.320	0.638	0.838 (0.363)
	BPMN (n=35)	0.260	0.611		0.200	0.473	
Problem solving (unacceptable answers)	EPC (n=34)	0.850	0.989	0.707 (0.403)	1.210	1.200	0.546 (0.463)
	BPMN (n=35)	1.060	1.027		0.910	1.067	
Cloze (correct answers)	EPC (n=34)	9.350	2.695	0.017 (0.896)	8.350	4.119	0.051 (0.822)
	BPMN (n=35)	9.260	3.320		8.570	3.920	

H1a hypothesized higher problem solving scores for the EPC group. As can be seen from Table 2, however, results between the EPC and the BPMN group did not vary significantly. For both cases, in fact, the BPMN group achieved higher test scores for plausible answers that were not directly inferable from the model. Scores for acceptable model-based answers were higher for the EPC group, though not significantly. H1b hypothesized higher Cloze test scores for the EPC group, yet again, Table 2 shows no significant differences in the results.

If the non-significant results would stem from an informational superiority of the BPMN model over the EPC group, then hypothesis H2 would not be supported and model comprehension scores should be significantly different between the two groups. While Table 2 shows that the EPC group achieved higher comprehension scores than the BPMN group, the differences were not significant at $\alpha = 0.05$ and hence, H2 would appear to be supported and indicates that the models used are in fact informationally equivalent.

Other factors that might explain the non-significant differences in scores were also considered. First, the two languages used to create the models might be computationally different, which would result in differences in the time taken to complete the tasks. Longer time to complete the tasks might indicate higher complexity of one of the models, which could confound the results. Alternatively, it might indicate that participants simply took more time to prepare the answer, which potentially leads to better answers. Another potential implication, as suggested by hypotheses H3a, H3b and H3c, might be that due to less apparent complexity and increased familiarity with one model type, participants would be quicker in developing answers. Yet, Table 3 shows that there are no significant differences between the two treatment groups in times to complete the various tasks.

Another factor might have been that the layout of the models could be more conducive to some participants, resulting in differences in the ease of understanding the models. For this reason, the post-test collected data on the perceived ease of model understanding using a Likert-type scale similar to the one used by Gemino and Wand (2005). Again, differences were non-significant, as shown in Table 3.

Table 3: Means and standard deviations of time taken to complete tasks and ease of understanding

Measure	Group	Case: Goods receipt			Case: Claims handling		
		Means	Standard deviation	F (Sig.)	Means	Standard deviation	F (Sig.)
Time taken to complete model comprehension task (min)	EPC (n=34)	4.060	1.413	1.469 (0.230)	3.190	1.176	0.151 (0.699)
	BPMN (n=35)	3.680	1.173		3.330	1.780	
Time taken to complete problem solving task (min)	EPC (n=34)	6.660	2.647	0.767 (0.384)	4.680	1.982	.546 (0.463)
	BPMN (n=35)	7.300	3.264		4.290	1.997	
Time taken to complete Cloze task (min)	EPC (n=34)	3.780	1.385	0.070 (0.793)	3.340	1.495	1.739 (0.193)
	BPMN (n=35)	3.870	1.310		3.930	1.870	
Ease of understanding	EPC (n=34)				4.721	0.638	.164 (0.687)
(1=strongly disagree, 7=strongly agree)	BPMN (n=35)				4.184	0.610	

What do the Results Imply?

Our results are indeed surprising. One would have expected differences to manifest between the two model groups. Admittedly, differences exist, yet, are neglectible in their significance. This implies that process modellers with training in any process modelling language perform reasonably well in understanding other process models. Why would that be?

One could obviously argue that our experiment is flawed because BPMN and EPC are so similar that modellers can instantly translate between the two. Yet, this is not the case. Most obviously, EPC models follow a event-function-event alternation paradigm while BPMN is message- and flow-oriented. While this difference stems from practical observation, also a range of research has been conducted to establish differences between process modelling languages, and found that there are quite substantial differences between BPMN and EPC.

For example, one way of establishing differences in the expressive power of process modelling languages is by way of workflow pattern analysis. The workflow patterns framework developed by van der Aalst et al. (2003) and extended by Russell et al. (2006) focuses on how well process modelling languages provide support for a set of control flow, data and resource patterns, based on the assumption that a more complete coverage of these patterns leads to languages with advanced expressive power. This framework has been applied in the analysis of numerous process modelling languages including also EPCs and BPMN (Russell *et al.*, 2006). The examination of BPMN revealed that BPMN natively provides clear support for 24 of 43 patterns, 8 patterns are somewhat supported and another 11 patterns are clearly not supported. This is far better support than that of EPCs (ten patterns clearly supported, two somewhat supported and 31 unsupported), which in turn implies clear differences in their expressive power and, consequently, also in their complexity.

Along similar lines, a second increasingly popular evaluation framework for process modelling languages has become known as representational analysis based on foundational ontologies (Rosemann *et al.*, forthcoming). This type of analysis focuses to establish representational differences between process modelling languages in the way they facilitate complete and clear descriptions of real-world domains. Similar to the case of the workflow patterns, analyses of BPMN (Recker *et al.*, 2006) and EPCs (Green and Rosemann, 2000) were conducted. The comparative analysis performed by Rosemann et al. (2006) clearly describes how BPMN is superior to EPCs in facilitating theoretically complete descriptions of real-world domains.

Since there are considerable differences between the two process modelling languages, the insignificant differences between understanding BPMN and EPC models by EPC modellers remain unexplained. It would appear, in fact, that the process of learning to developing an understanding of process models is not dependant on the underlying language at all.

A second attempt at explaining the insignificant differences in understanding BPMN and EPC models by EPC modellers may consider cognitive fit theory (Vessey and Galletta, 1991). This theory suggests that apart from the representation of a content (or problem), also the nature of the task and the set of skills by the task solver should be examined (Agarwal *et al.*, 1996). A proposition based upon the theory of cognitive fit would be that it is the type of process modelling task (e.g., workflow specification versus process simulation versus process re-engineering) that influences the way we achieve learning performance. This would imply that in process modelling courses more emphasis must be put into discussing how process models are applied for various purposes rather than focusing on the semantics of certain languages, methods or tools. This proposition, obviously, remains to be tested in future work. In the present study, we used an identical set of tasks for which process modelling was conducted and found that there were no significant differences in the outcomes. It is possible that we would have obtained a different picture if the process modelling tasks were different.

A third attempt to explain the lack of significant differences in process model understanding could rely in the observation that process modelling is a paradigmatically different way of modelling when compared to object-oriented or data modelling (Vessey and Conger, 1993). When acquiring process modelling skills (taught in whatever language), learning individuals adopt a particular worldview of modelling, e.g., they start appreciating real-world domains in timely ordered series of activities, events and messages, that is, a process-aware perspective. This dynamic perspective is paradigmatically different than a static perspective in data modelling. Assuming that a set of individuals would adopt the same way of modelling worldview, it would sound only reasonable to suspect that the way the express these worldviews would not depend on the graphical language in use. Instead, it would lead to the question of how different paradigmatic views on process modelling would lead to changes in learning outcomes. In other words, we can speculate that the way complex real-world phenomena are understood and represented in the internal mind models of an individual may have a stronger impact on what can be understood from an externalized description in the form of a process model. This would imply that research should focus more the question of how different modelling worldviews are developed by participants and how the way of ‘thinking in processes’ can best be taught and explained.

In summary, the research presented in this paper can only be a first step towards a deeper investigation of how learning process modelling works. Yet, we have laid an empirical basis of knowledge based on which new propositions and hypotheses can be generated to study different factors, such as the ones briefly discussed above, that may have led to the results we obtained.

Conclusions

In this paper we reported on the design and conduct of an experiment related to learning process modelling languages. We considered one element involved in the learning process as suggested by Mayer (1989), that is, content presentation. Based on CTML we introduced a range of hypotheses, elaborated on an empirical study in which we tested them, described the results and speculated on the implications of these results. What remains for this section is a discussion on the immediate conclusions for academia and practise that can be drawn from the body of knowledge we established with our experiment.

Implications for Academia

Our research results have implications primarily with respect to educational aspects. We have shown that users of EPCs understand BPMN diagrams equally well even though they were never exposed to this modelling language before. With respect to the university curriculum it must be concluded that it is neither of much use to include several process modelling languages into a single course, nor is it of much use to impose an obligation on students to learn several process modelling languages in several courses.

Additionally, as mentioned above, our research raises another very important and interesting question: Can we build families of process modelling languages with the following properties: Language users of one process modelling language can easily switch to another language of the same family and have difficulties to switch to a language from another family. It seems likely that the results of this study can be replicated for other process modelling languages in which activities and events play a central role. But is it possible to replicate these results, e.g., for Petri nets, or are Petri nets so fundamentally different from BPMN and EPCs that our obtained results would not hold again?

A third implication for academia is to face the question of how process modelling learning outcomes are actually achieved. The cognitive theory of multimedia learning used in this paper suggests three elements involved in the process: content, content presentation and user characteristics (Mayer, 1989). We have focused the element content presentation in our study and controlled for content and user characteristics. The next step would then be to study different types of content and different types of user characteristics, respectively. Could it be that certain types of process modellers are more receptive to certain process modelling tasks? Some prior studies in IS, e.g., (Vessey and Galletta, 1991; Vessey and Conger, 1994; Khatri *et al.*, 2006), indeed suggest that user differences in cognitive abilities, application domain knowledge and method knowledge affect the way that conceptual modelling and information acquisition is conducted. An important research question would then be to investigate how these user characteristics impact the way process modelling is conducted.

Implications for Practice

The main implication for practice is the insight that a new process modelling language does not pose an economic threat to an organization if the majority of BPM actors within this organization are users of a different process modelling language. It would appear that there is no immediate need for organizations to embark on extensive training courses every time the process modelling language in use has to be changed. Instead our findings suggest that a set of analysts equipped with adequate skills in one process modelling language will be fit to understand other process models too.

For the provider side our results suggest that carefully managed changes to process modelling languages are not unlikely to be accepted by a customer base. Such changes may always be necessary in certain situations and should be seen as an opportunity rather than a problem. For instance, providers may find the need to enhance the expressive power of a process modelling language to be better equipped for future and advanced process modelling needs (e.g., advanced workflow execution, support for web service specification etc.). The resulting differences in expressiveness and complexity of the language appears to be well-absorbed by the existing language user communities.

References

Agarwal, R., Sinha, A.P. and Tanniru, M. (1996) Cognitive Fit in Requirements Modeling: A Study of Object and Process Methodologies, *Journal of Management Information Systems,* 13, 137-162.

Batra, D. and Davis, J.G. (1992) Conceptual Data Modelling in Database Design: Similarities and Differences between Expert and Novice Designers, *International Journal of Man-Machine Studies,* 37, 83-101.

Batra, D., Hoffler, J.A. and Bostrom, R.P. (1990) Comparing Representations with Relational and EER Models, *Communications of the ACM,* 33, 126-139.

Bodart, F., Patel, A., Sim, M. and Weber, R. (2001) Should Optional Properties Be Used in Conceptual Modelling? A Theory and Three Empirical Tests, *Information Systems Research,* 12, 384-405.

BPMI.org and OMG (2006) Business Process Modeling Notation Specification. Final Adopted Specification, URL http://www.bpmn.org, Accessed February 20.

Fowler, M. (2004) *UML Distilled: A Brief Guide To The Standard Object Modelling Language* (3rd edition), Addison-Wesley Longman, Boston, Massachusetts.

Gemino, A. (2004) Empirical Comparisons of Animation and Narration in Requirements Validation, *Requirements Engineering,* 9, 153-168.

Gemino, A. and Wand, Y. (2003) Evaluating Modeling Techniques based on Models of Learning, *Communications of the ACM,* 46, 79-84.

Gemino, A. and Wand, Y. (2004) A Framework for Empirical Evaluation of Conceptual Modeling Techniques, *Requirements Engineering,* 9, 248-260.

Gemino, A. and Wand, Y. (2005) Complexity and Clarity in Conceptual Modeling: Comparison of Mandatory and Optional Properties, *Data & Knowledge Engineering,* 55, 301-326.

Green, P. and Rosemann, M. (2000) Integrated Process Modeling. An Ontological Evaluation, *Information Systems,* 25, 73-87.

Greene, B.B. (2001) Testing Reading Comprehension of Theoretical Discourse with Cloze, *Journal of Research in Reading,* 24, 82-98.

Jarvenpaa, S.L. and Machesky, J.J. (1989) Data Analysis and Learning: An Experimental Study of Data Modeling Tools, *International Journal of Man-Machine Studies,* 31, 367-391.

Khatri, V., Vessey, I., V. Ramesh, P.C. and Sung-Jin, P. (2006) Understanding Conceptual Schemas: Exploring the Role of Application and IS Domain Knowledge, *Information Systems Research,* 17, 81-99.

Mayer, R.E. (1989) Models for Understanding, *Review of Educational Research,* 59, 43-64.

Mayer, R.E. (2001) *Multimedia Learning,* Cambridge University Press, Cambridge, Massachusetts.

Moody, D.L. (2005) Theoretical and Practical Issues in Evaluating the Quality of Conceptual Models: Current State and Future Directions, *Data & Knowledge Engineering,* 15, 243-276.

Moore, G.C. and Benbasat, I. (1991) Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation, *Information Systems Research,* 2, 192-222.

Petri, C.A. (1962) "Fundamentals of a Theory of Asynchronous Information Flow" in C. M. Popplewell (ed.) *IFIP Congress 62: Information Processing*, North-Holland, Munich, Germany, 386-390.

Rankin, E.F. and Culhane, J.W. (1969) Comparable Cloze and Multiple-Choice Comprehension Test Scores, *Journal of Reading,* 13, 193-198.

Recker, J., Indulska, M., Rosemann, M. and Green, P. (2006) "How Good is BPMN Really? Insights from Theory and Practice" in J. Ljungberg and M. Andersson (eds.) *Proceedings of the 14th European Conference on Information Systems*, Association for Information Systems, Goeteborg, Sweden, 1582-1593.

Rosemann, M., Green, P., Indulska, M. and Recker, J. (forthcoming) Using Ontology for the Representational Analysis of Process Modeling Techniques, *International Journal of Business Process Integration and Management*, in press.

Rosemann, M., Recker, J., Indulska, M. and Green, P. (2006) "A Study of the Evolution of the Representational Capabilities of Process Modeling Grammars" in E. Dubois and K. Pohl (eds.) *Advanced Information Systems Engineering - CAiSE 2006*, Springer, Luxembourg, Grand-Duchy of Luxembourg, 447-461.

Russell, N., ter Hofstede, A.H.M., van der Aalst, W.M.P. and Mulyar, N.A. (2006) *Workflow Control-Flow Patterns: A Revised View,* BPM Center Report No. BPM-06-22, BPMcenter.org.

Scheer, A.-W. (2000) *ARIS - Business Process Modeling* (3rd edition)*,* Springer, Berlin, Germany.

Siau, K. (1999) Information Modeling and Method Engineering: A Psychological Perspective, *Journal of Database Management,* 10, 44-50.

Siau, K. (2004) Informational and Computational Equivalence in Comparing Information Modeling Methods, *Journal of Database Management,* 15, 73-86.

Siau, K. and Loo, P.-P. (2006) Identifying Difficulties in Learning UML, *Information Systems Management,* 23, 43-51.

Sinur, J. (2004) *Magic Quadrant for Business Process Analysis,* Gartner Research Note No. M-22-0651 March, Gartner, Inc, Stamford, Connecticut.

Stevens, J.P. (2001) *Applied Multivariate Statistics for the Social Sciences* (4th edition)*,* Lawrence Erlbaum Associates, Hillsdale, New Jersey.

Taylor, W.L. (1953) Cloze Procedure: A New Tool For Measuring Readability, *Journalism Quarterly,* 30, 415-433.

van der Aalst, W.M.P. and ter Hofstede, A.H.M. (2005) YAWL: Yet Another Workflow Language, *Information Systems,* 30, 245-275.

van der Aalst, W.M.P., ter Hofstede, A.H.M., Kiepuszewski, B. and Barros, A.P. (2003) Workflow Patterns, *Distributed and Parallel Databases,* 14, 5-51.

Vessey, I. and Conger, S.A. (1993) Learning to Specify Information Requirements: The Relationship between Application and Methodology, *Journal of Management Information Systems,* 10, 177-202.

Vessey, I. and Conger, S.A. (1994) Requirements Specification: Learning Object, Process, and Data Methodologies, *Communications of the ACM,* 37, 102-113.

Vessey, I. and Galletta, D.F. (1991) Cognitive Fit: An Empirical Study of Information Acquisition, *Information Systems Research,* 2, 63-84.

Copyright